User-relative Personalized Tour Recommendation

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ABSTRACT

Tour planning and recommendation is an important but tedious task for tourists visiting unfamiliar cities and places. While there are various personalized tour recommendation works, they typically adopt a simple measure of user interests based on the number of times a user has visited a place. In this paper, we propose an improved personalized tour recommendation system that considers a user's interest preferences in specific categories, relative to his/her overall interests. Using a Flickr dataset across eight cities, we compared our proposed algorithm against various baselines and experimental results show that our algorithm obtained superior performance in terms of user interest and popularity.

CCS CONCEPTS

• **Information systems → Personalization**; **Recommender systems**; *Location based services*; *Data mining*; Web applications.

KEYWORDS

Tour Recommendations; Trip Planning; Recommendation Systems; Personalization

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1 INTRODUCTION

Tour planning is an important task for ensuring satisfactory visits to unfamiliar cities and places. However, visitors are faced with the challenge of identifying popular places aligned with their personal interests. In addition, there is an added complexity due to the need to schedule visits to all recommended places while considering the available tour budget, time and cost.

There is an abundance of information available on Internet about travel guides and famous places, but they do not consider the user's personal interests and preferences nor contemplate the trip's constraints like time and cost. Despite the availability of such online information, people may end up spending excessive efforts and time to plan their itinerary, and yet end up with an undesired itinerary thus leaving them with an unsatisfactory and frustrating experience.

In recent times, personalized tour recommendation systems have benefited from the advancement in web technologies and geo-location services. The large amount of online available geo-tagged photos facilitate the modelling of user interest, preferences and trip constraints while strategizing itinerary planning. While many works consider user interest, they adopt a simple measure based on the number of times a user has visited a place.

Contributions

Unlike earlier works that adopt a simplistic definition of user interest based on visit counts, this paper proposes a tour recommendation system that utilizes a novel user-relative measure of interest preferences build upon the Orienteering problem.

We propose two variation of user-specific interest preferences. The first approach aims to recommend an itinerary with no prior knowledge about the user by taking advantage of the large collection of geo tagged photos available online. Based on photo frequencies of each POI by all users, it determines the popularity of each POI and suggests the itinerary based on most popular POIs. The second approach aims to improve upon the targeted personalization level for each user. The benefits of this approach include having a tour itinerary that is customized for each user and caters to the user's categories of interest. For example, in a city full of many tourist attractions, this approach caters to specific category the user is interested in. For example, if a user has shown to prefer outdoors and beaches more than museums and multiplexes, then the recommendation system takes that into account while building the itinerary.

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2 RELATED WORK

Orienteering problem overview

Orienteering problem is a routing problem which can be viewed as a contest with multiple nodes, where each node has some specific score. The goal of the contest is to maximize the total score which is gathered by visiting different nodes. The contest is time constrained, which needs a strategical plan to choose a subset of nodes visit in sequence, to maximize collected budget within given time and budget [23]. For a detailed review of Orienteering problem, [13, 23, 25] reviews orienteering problem and its applications, discusses and compares published approaches and heuristics of Orienteering problem.

Tour recommendation variants

Tour recommendation is a well-studied field that typically focus on maximizing user preferences within the given trip constraints [6, 14, 15, 17, 19]. For example, [1] proposed a POI recommender system based on offline modelling (user preferences learnt from her location history) and online recommendation (social opinions learnt from location history of 'local experts'). [3] modelled tour recommendation as an instance of the Generalized Maximum coverage problem. Building on the same, [5] suggested a solution by exploiting an instance of Traveling Salesman Problem (TSP). Others modelled the tour recommendation problem as an instance of the Orienteering problem [9, 10], and various variations based on specific POI visit sequences [12] and POI category constraints [2]. A unique method of using POIs and route information as features to a machine learning algorithm to recommend probable tour routes was proposed by [8]. Various works also considered real life constraints like POI availability and travelling time uncertainty [29, 30], queuing time awareness [16], visit duration and recency [18], pedestrian crowdedness [26], transport costs [11]. Similarly, various web and mobile applications have been developed for tour recommendation purposes [4, 7, 20, 24, 27].

Differences with earlier work. Our proposed work differs from these earlier works in several aspects. We automatically derive a measure of user-based interest from the user's photo frequency at POIs of a specific category, relative to: (i) The average photo frequencies of other users at that POI; and (ii) The average photo frequency of that user at all POIs. In contrast, these earlier works either use time-based user interest, frequency-based user interest or explicitly mentioned user interest preferences. In addition, we improve upon the targeted personalization level for each user by recommending customized itineraries that cater to the user interest categories.

3 PROBLEM FORMULATION AND ALGORITHMS

Problem Formulation. Similar to many earlier works [18, 21], we model our recommendation problem based on a variant of the Orienteering problem [13, 23, 25]. In this tour recommendation problem, our main objective is to recommend a tour itinerary $I = (p_1, ..., p_N)$ that maximizes the total profit from visiting the list of POIs p_1 to P_N, while ensuring that the tour itinerary can be completed within a specific time budget B. Given a set of POIs P, we optimize for:

$$Max \sum_{p_i \in P} \sum_{p_j \in P} Path_{p_i,p_j} \Big(\eta Int_u(p_i) + (1-\eta) Pop(p_i)\Big) \quad (1)$$

where $Path_{p_i,p_j} = 1$ if a path between POI p_i and p_j is selected as part of the itinerary, and $Path_{p_i,p_j} = 0$ otherwise. $Int_u(p_i)$ represents a user-specific interest score of how interesting POI p_i is to user u, while $Pop(p_i)$ indicates the general popularity of POI p_i. In addition, Equation 1 is subjected to the following constraints: (i) starting and ending at specific POIs; (ii) connectivity of POIs in the itinerary; (iii) completing the itinerary within a specific time or distance budget B.

In addition, Equation 1 is subjected to the following constraints:

$$\sum_{p_i \in I} Path_{p_s,p_i} = \sum_{p_j \in I} Path_{p_j,p_d} = 1 \quad (2)$$

Constraint 2 ensures that the recommended itinerary starts at a specific POI p_s, and ends at another specific POI p_d. In real-life, this starting and destination POIs would correspond to POIs near the hotel that a tourist is staying at.

$$\sum_{p_i,p_k \in I} Path_{p_i,p_k} = \sum_{p_j,p_k \in I} Path_{p_k,p_j} \leq 1 \quad (3)$$

Constraint 3 ensures that the recommended itinerary fulfills two conditions, namely: (i) all selected paths are connected as a full itinerary; and (ii) no POIs are visited more than once.

$$\sum_{p_i \in I} \sum_{p_j \in I} Cost(p_i, p_j) Path_{p_i,p_j} \leq B \quad (4)$$

Constraint 4 ensures that the recommended itinerary can be completed within a specific time or distance budget B.

Algorithms and Baselines. We developed an Integer program to solve the problem defined in Section 3, along with novel approaches to defining user interest preferences. The two proposed approaches based on photo frequency are as follows:

(i) POI based Photo frequency (PF_P): Given a set of travel history of all users U, the system determines the popularity of the POI using average photo frequency at each POI.
(ii) User based photo frequency (PF_U): Given a set of travel history of a user u, the system determines the popularity of that category of POI for the user using average photos taken by that user at that category of the POI.

In a city, there can be multiple categories of places comprising of multiple POIS. Consider m POIs for a particular city. Let $P = \{p_1, .., p_m\}$ be the set of POIs in that city. Each POI p has a category Cat_p (e.g., church, park, beach) and latitude/longitude coordinates associated with it. The popularity function $Pop(p)$ that indicates the popularity of a POI p, based on the average frequency of photos clicked at that POI. We now introduce the key notations and definitions used in this work.

Definition 1: Travel History.

(1) PF_P: Given a user u who has visited n POIs, the travel history is modelled as an ordered sequence, $S_{ph} = ((p_1, fph_{p1}), (p_2, fph_{p2})...)$, with each duplet (p_x, fph_{px}) comprising the visited POI p_x, and number of photos at POI p_x.
(2) PF_U: Given a POI p visited by n users, the travel record of POI p is modelled as an ordered sequence, $S_{ph} = ((u_1, fph_{u_1}), (u_2, fph_{u_2})...)$, with each duplet (u_x, fph_{u_x}) comprising the user u_x, and number of photos taken by u_x.

Definition 2: Average POI Photo Frequency.

(1) PF_P: Given a set of travel history of all users U, the system determines the popularity of the POI using average photo frequency at each POI.

$$\overline{ph}(p) = \frac{1}{n} \sum_{u \in U} \sum_{p_x \in S_{ph}} (fph_{px}) \delta(P_x = P) \forall p \in P \tag{5}$$

where n is the number of photos at POI p by all users U and $\delta(p_x = p) = 1$, if $p_x = p$ and 0, otherwise.

(2) PF_U: Given a set of travel record for all POIs P, we determine the preference of user u using average photo frequency of user u at all POIs P.

$$\overline{ph}(u) = \frac{1}{n} \sum_{p \in P} \sum_{u_x \in S_{ph}} (fph_{u_x}) \delta(U_x = U) \, \forall u \in U \tag{6}$$

where n is the number of photos taken by user u at all POIs P and $\delta(u_x = u) = 1$, if $u_x = u$ and 0, otherwise.

In tour recommendation problems, the user interest preferences are typically derived from POI visit frequency [3, 5, 8, 16]. In contrast, we consider a user's POI visit frequency relative to the average visit frequency for a better personalization.

Definition 3: Photo Frequency based User Interest.

As described earlier, the category of a POI p is denoted as Cat_p. Given that C represents the set of all POI categories, the interest of a user u in POI category c is determined as follows:

(1) PF_P:

$$Int_u^{fph}(c) = \sum_{p_x \in S_{ph}} \frac{(fph_{px})}{\overline{ph}(p_x)} \delta(Cat_{px} = C) \, \forall c \in C \tag{7}$$

where $\delta(Cat_{px} = C) = 1$, if $Cat_{px} = C$ and 0, otherwise.

(2) PF_U:

$$Int_u^{fph}(c) = \sum_{u_x \in S_{ph}, p \in P} \frac{(fph_{ux})}{\overline{ph}(u_x)} \delta(Cat_p = C) \, \forall c \in C \tag{8}$$

where $\delta(Cat_p = C) = 1$, if $Cat_p = C$ and 0, otherwise.

Briefly, the above equations model the interest of a user in a particular POI category c based on photo frequency at each POI of category c, relative to the average photo frequency (of all users and a single user) at the same POI. The reason is that a user is likely to click more photos of the POI that he/she is interested in.

Hence, firstly by calculating how many more (or less) photos a user has taken, the interest level of this user in POIs of this category can be determined. Secondly, by calculating how many more (or less) photos have been taken by all users, the overall interest level of all users in POIs of this category can be determined.

4 EXPERIMENT METHODOLOGY

Dataset. For our experiments, we utilized the Yahoo! Flickr Creative Commons 100M dataset [22, 28], focusing on a dataset of 814k geo-tagged photos across eight cities including Toronto, Osaka, Glasglow, Budapest, Perth, Vienna, Delhi and Edinburgh. As provided in [18], these geotagged photos were mapped to a list of POIs based on their respective Wikipedia entries, i.e., proximity of geo-tagged photos to Wikipedia entries of POIs based on their latitude/longitude coordinates. Similarly, the categories of POIs are based on their respective Wikipedia entries. The dataset also comprises information like the geo-location coordinates, date/timestamp of the photos taken. To ensure accuracy and generalizability of results, only photos with the highest geo-location accuracy have been chosen.

Evaluation and Metrics. We evaluated our algorithm and the baselines using leave-one-out cross-validation, which involves evaluating a specific travel sequence of a user while using his/her other travel sequences as training data. The

Table 1: Comparison between Time-based User Interest ($PT-.5T$ and $PT-1T$), Photo Frequency-based User Interest with respect to all users ($PT-.5P_A$ and $PT-1P_A$) and Photo Frequency-based User Interest with respect to a single user ($PT-.5P_U$ and $PT-1P_U$).

Osaka					
Algorithm	Popularity	Interest	Precision	Recall	F1 Score
$PT-.5P_U$	1.107 ± .939	1.551 ± .228	0.652 ± .037	0.739 ± .027	0.685 ± .033
$PT-1P_U$	0.772 ± 0.068	1.576 ± .228	0.581 ± .032	0.661 ± .024	0.608 ± .028
$PT-.5P_A$	1.118 ± .093	1.652 ± .235	0.650 ± .037	0.752 ± .025	0.689 ± .032
$PT-1P_A$	0.772 ± .067	1.683 ± .237	0.585 ± .032	0.676 ± .023	0.618 ± .027
$PT-.5T$	1.144 ± .092	1.171 ± .205	0.662 ± .037	0.759 ± .026	0.699 ± .033
$PT-1T$	0.737 ± .067	1.205 ± .211	0.622 ± .032	0.682 ± .025	0.641 ± .029

Toronto					
Algorithm	Popularity	Interest	Precision	Recall	F1 Score
$PT-.5P_U$	2.015 ± .062	1.803 ± .084	0.680 ± .013	0.761 ± .009	0.709 ± .011
$PT-1P_U$	1.574 ± .047	1.898 ± .088	0.675 ± .013	0.730 ± .010	0.691 ± .011
$PT-.5P_A$	2.022 ± .064	1.863 ± .086	0.679 ± .013	0.763 ± .009	0.710 ± .011
$PT-1P_A$	1.517 ± .047	2.012 ± .089	0.672 ± .013	0.730 ± .010	0.689 ± .011
$PT-.5T$	1.960 ± .064	1.223 ± .061	0.706 ± .013	0.779 ± .010	0.732 ± .012
$PT-1T$	1.420 ± .043	1.350 ± .069	0.710 ± .013	0.744 ± .011	0.718 ± .012

Glasgow					
Algorithm	Popularity	Interest	Precision	Recall	F1 Score
$PT-.5P_U$	1.552 ± .126	1.181 ± .216	0.744 ± .030	0.806 ± .021	0.766 ± .026
$PT-1P_U$	1.113 ± .093	1.199 ± .205	0.708 ± .030	0.730 ± .024	0.707 ± .027
$PT-.5P_A$	1.591 ± .947	1.077 ± 1.511	0.764 ± .225	0.802 ± .185	0.764 ± .225
$PT-1P_A$	1.075 ± .087	1.151 ± .192	0.708 ± .029	0.728 ± .024	0.708 ± .026
$PT-.5T$	1.578 ± .125	0.614 ± .106	0.778 ± .028	0.821 ± .020	0.794 ± .025
$PT-1T$	1.001 ± .066	0.676 ± .135	0.736 ± .030	0.739 ± .026	0.727 ± .027

Edinburgh					
Algorithm	Popularity	Interest	Precision	Recall	F1 Score
$PT-.5P_U$	1.961 ± .052	2.499 ± .115	0.599 ± .012	0.729 ± .008	0.645 ± .010
$PT-1P_U$	1.482 ± .050	2.543 ± .123	0.558 ± .012	0.664 ± .009	0.590 ± .010
$PT-.5P_A$	1.975 ± .042	2.525 ± .092	0.594 ± .010	0.726 ± .007	0.641 ± .009
$PT-1P_A$	1.461 ± .049	2.582 ± .125	0.554 ± .012	0.662 ± .009	0.587 ± .010
$PT-.5T$	2.007 ± .054	1.568 ± .089	0.652 ± .012	0.739 ± .008	0.670 ± .010
$PT-1T$	1.297 ± .049	1.660 ± .103	0.594 ± .011	0.660 ± .010	0.611 ± .010

Perth					
Algorithm	Popularity	Interest	Precision	Recall	F1 Score
$PT-.5P_U$	1.847 ± .190	1.680 ± .263	0.693 ± .047	0.772 ± .037	0.722 ± .042
$PT-1P_U$	1.289 ± .166	1.765 ± .332	0.626 ± .040	0.694 ± .036	0.650 ± .037
$PT-.5P_A$	1.786 ± .195	2.025 ± .302	0.680 ± .051	0.780 ± .037	0.718 ± .045
$PT-1P_A$	1.283 ± .196	1.988 ± .271	0.610 ± .049	0.697 ± .038	0.641 ± .043
$PT-.5T$	1.828 ± .168	1.595 ± .206	0.759 ± .041	0.827 ± .029	0.784 ± .036
$PT-1T$	1.274 ± .170	1.710 ± .272	0.677 ± .047	0.740 ± .038	0.699 ± .042

Delhi					
Algorithm	Popularity	Interest	Precision	Recall	F1 Score
$PT-.5P_U$	1.647 ± .166	1.294 ± .316	0.731 ± .047	0.804 ± .034	0.757 ± .041
$PT-1P_U$	1.139 ± .145	1.422 ± .352	0.610 ± .042	0.671 ± .036	0.630 ± .038
$PT-.5P_A$	1.559 ± .134	1.275 ± .334	0.727 ± .047	0.793 ± .036	0.750 ± .042
$PT-1P_A$	1.130 ± .109	1.332 ± .346	0.614 ± .038	0.676 ± .030	0.636 ± .034
$PT-.5T$	1.610 ± .133	0.954 ± .252	0.746 ± .045	0.807 ± .036	0.769 ± .041
$PT-1T$	1.128 ± .100	1.000 ± .256	0.632 ± .042	0.674 ± .036	0.648 ± .039

Budapest					
Algorithm	Popularity	Interest	Precision	Recall	F1 Score
$PT-.5P_U$	2.871 ± .297	3.254 ± .454	0.520 ± .038	0.662 ± .024	0.568 ± .033
$PT-1P_U$	2.106 ± .293	3.216 ± .486	0.503 ± .042	0.616 ± .031	0.530 ± .037
$PT-.5P_A$	2.697 ± .308	3.357 ± .484	0.524 ± .037	0.653 ± .025	0.568 ± .032
$PT-1P_A$	2.082 ± .286	3.402 ± .490	0.499 ± .043	0.614 ± .031	0.536 ± .037
$PT-.5T$	2.791 ± .293	1.850 ± .309	0.551 ± .042	0.663 ± .028	0.589 ± .036
$PT-1T$	1.806 ± .226	2.019 ± .334	0.558 ± .037	0.624 ± .029	0.580 ± .032

Vienna					
Algorithm	Popularity	Interest	Precision	Recall	F1 Score
$PT-.5P_U$	1.513 ± .052	2.470 ± .122	0.604 ± .013	0.707 ± .010	0.637 ± .012
$PT-1P_U$	1.175 ± .049	2.561 ± .134	0.562 ± .012	0.652 ± .010	0.588 ± .011
$PT-.5P_A$	1.573 ± .052	2.460 ± .126	0.614 ± .013	0.710 ± .010	0.644 ± .012
$PT-1P_A$	1.168 ± .049	2.608 ± .134	0.562 ± .012	0.652 ± .009	0.587 ± .011
$PT-.5T$	1.577 ± .054	1.576 ± .103	0.629 ± .013	0.713 ± .010	0.656 ± .011
$PT-1T$	1.022 ± .042	1.690 ± .111	0.596 ± .012	0.651 ± .010	0.609 ± .011

starting/ending POI and travel duration are set to that of the specific travel sequence being evaluated, which is used as a representation of a person's real-life visit. The following evaluation metrics were used:

(1) **Tour Popularity:** $T_{pop}(I)$. The total popularity of all POIs in itinerary I.
(2) **Tour Interest:** $T^{u}_{Int}(I)$. The total interest of all POIs in itinerary I to user u.
(3) **Tour Precision:** $T_p(I)$. The proportion of POIs recommended in itinerary I, which matched user's real-life travel sequence.
(4) **Tour Recall:** $T_r(I)$. The proportion of POIs in a user's actual travel sequence that were also recommended in itinerary I.
(5) **Tour F_1−score:** $T_{F_1}(I)$. The harmonic mean of both the recall and precision of a recommended tour itinerary I.

5 RESULTS AND DISCUSSION

Table 1 show the comparison between Time-based User Interest ($PT-.5T$ and $PT-1T$), Photo Frequency-based User Interest with respect to all users ($PT-.5P_A$ and $PT-1P_A$) and Photo Frequency-based User Interest with respect to single user ($PT-.5P_U$ and $PT-1P_U$). Overall results show that our Photo Frequency-based algorithms outperform the baselines in terms of popularity and interest, while offering comparable performance in terms of other metrics.

Comparison of Popularity and Interest. In terms of Interest (T_{int}) metric, the proposed algortihms outperform the baselines in all the cities, with $PT-1P_A$ being the best performing algorithm, followed by $PT-1P_U$. In terms of Popularity (T_{pop}) metric, $PT-.5P_U$ performs equally good as the baseline $PT-.5T$. In four cities $PT-.5P_U$ performs the best and in other four $PT-.5T$. The results show that the Photo Frequency-based algorithms reflects on the overall popularity and overall interests of the POIs better than the baselines, for recommending itineraries.

Comparison between Time based and Photo-Frequency based User Interest. With regards to precision (T_p), recall (T_r) and f1-score (T_{F_1}) the proposed algorithms outperform one of the baselines ($PT-1T$) in all the cities, standing the second best. In terms of T_p, $PT-.5P_U$ performs the second best in five cities, followed by $PT-.5P_A$ performing the second best in one city. In terms of T_r, $PT-.5P_U$ performs the second best in four cities and $PT-.5P_A$ performs the second best in rest four. Here, $PT-.5P_U$ and $PT-.5P_A$ perform equally good. These two proposed algorithms outperform the baseline ($PT-1T$) with regards to recall. In concern to the F1-score T_{F_1} metric, the proposed algorithm $PT-1P_A$ performs the best on one city, $PT-.5P_U$ performs the second best in five cities, followed by $PT-.5P_A$ performing the second best in two cities. The results show that the proposed algorithms outperforms the baselines in most cities in terms of popularity and interest. The algorithms ($PT-.5P_U$ and $PT-.5P_A$) outperform one baseline, performing second best in terms of precision, recall and f1-score.

6 CONCLUSION AND FUTURE WORK

We modelled our tour recommendation problem as an instance of the Orienteering problem and proposed two algorithms for recommending personalized tours. We recommend suitable POIs using both photo frequency user interest preference and POI popularity. We used geo-tagged photos to determine the photo frequency of the user and automatically derive user interest and POI popularity to train the algorithms. Our work improves upon the previous research in following ways: (i) We introduce photo frequency based user interest derived from the number of photos taken by the user at a POI of a specific category, unlike earlier works which consider time-based or frequency-based user interest; and (ii) We improve upon the targeted personalization level for each user by recommending customized itineraries that cater to the user interest preferences learnt from the user photo frequency dataset. Using Flickr dataset across eight cities, we evaluate our algorithms in terms of precision, recall, F1-score, tour popularity and interest. The results show that: (i) Using photo-frequency based user interest outperform the baselines in all cities in terms of interest. It is at par with the baselines in terms of tour popularity by sharing equal stand; and (ii) The proposed algorithms outperform one of the baseline algorithms of time-based user interest in terms of overall precision, recall and F1-score.

In this work, our focus was to recommend user-relative personalized tour itineraries. Some possible future work directions are: (i) Using sentiment awareness on content obtained from location based social network tags to combine sentiment analysis techniques with personalization approaches and path planning algorithms for recommending itineraries that consider user interest preferences and sentiments; and (ii) Recommending tour itineraries by considering the public transport arrival and departure time to facilitate realistic tour planning and minimize public transport waiting time. Moreover, real time uncertainty of public transport could be modelled to improve the suitability.

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REFERENCES

[1] Jie Bao, Yu Zheng, and Mohamed F. Mokbel. 2012. Location-based and preference-aware recommendation using sparse geo-social networking data. In *Proceedings of the 20th International Conference on Advances in Geographic Information Systems (SIGSPATIAL'12)*. 199–208.

[2] Paolo Bolzoni, Sven Helmer, Kevin Wellenzohn, Johann Gamper, and Periklis Andritsos. 2014. Efficient itinerary planning with category constraints. In *Proceedings of the 22nd ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems (SIGSPATIAL'14)*. 203–212.

[3] Igo Brilhante, Jose Antonio Macedo, Franco Maria Nardini, Raffaele Perego, and Chiara Renso. 2013. Where shall we go today? Planning touristic tours with TripBuilder. In *Proceedings of the 22nd ACM International Conference on Information and Knowledge Management (CIKM'13)*. 757–762.

[4] Igo Brilhante, Jose Antonio Macedo, Franco Maria Nardini, Raffaele Perego, and Chiara Renso. 2014. TripBuilder: A Tool for Recommending Sightseeing Tours. In *Proceedings of the 36th European Conference on Information Retrieval (ECIR'14)*. 771–774.

[5] Igo Ramalho Brilhante, Jose Antonio Macedo, Franco Maria Nardini, Raffaele Perego, and Chiara Renso. 2015. On planning sightseeing tours with TripBuilder. *Information Processing & Management* 51, 2 (2015), 1–15.

[6] Chao Chen, Daqing Zhang, Bin Guo, Xiaojuan Ma, Gang Pan, and Zhaohui Wu. 2015. TripPlanner: Personalized Trip Planning Leveraging Heterogeneous Crowdsourced Digital Footprints. *IEEE Transactions on Intelligent Transportation Systems* 16, 3 (2015), 1259–1273.

[7] Dawei Chen, Dongwoo Kim, Lexing Xie, Minjeong Shin, Aditya Krishna Menon, Cheng Soon Ong, Iman Avazpour, and John Grundy. 2017. PathRec: Visual Analysis of Travel Route Recommendations. In *Proceedings of the Eleventh ACM Conference on Recommender Systems (RecSys'17)*. 364–365.

[8] Dawei Chen, Cheng Soon Ong, and Lexing Xie. 2016. Learning Points and Routes to Recommend Trajectories. In *Proceedings of the 25th ACM*

International Conference on Information and Knowledge Management (CIKM'16). 2227–2232.

[9] Munmun De Choudhury, Moran Feldman, Sihem Amer-Yahia, Nadav Golbandi, Ronny Lempel, and Cong Yu. 2010. Automatic construction of travel itineraries using social breadcrumbs. In *Proceedings of the 21st ACM Conference on Hypertext and Hypermedia (HT'10)*. 35–44.

[10] Munmun De Choudhury, Moran Feldman, Sihem Amer-Yahia, Nadav Golbandi, Ronny Lempel, and Cong Yu. 2010. Constructing travel itineraries from tagged geo-temporal breadcrumbs. In *Proceedings of the 19th International Conference on World Wide Web (WWW'10)*. 1083–1084.

[11] Cheng-Yao Fu, Min-Chun Hu, Jui-Hsin Lai, Hsuan Wang, and Ja-Ling Wu. 2014. TravelBuddy: Interactive Travel Route Recommendation with a Visual Scene Interface. In *Proceedings of the 20th International Conference on Multimedia Modeling (MMM'14)*. 219–230.

[12] Aristides Gionis, Theodoros Lappas, Konstantinos Pelechrinis, and Evimaria Terzi. 2014. Customized tour recommendations in urban areas. In *Proceedings of the 7th ACM International Conference on Web Search and Data Mining (WSDM'14)*. 313–322.

[13] Aldy Gunawan, Hoong Chuin Lau, and Pieter Vansteenwegen. 2016. Orienteering Problem: A survey of recent variants, solution approaches and applications. *European Journal of Operational Research* 255, 2 (2016), 315–332.

[14] Takeshi Kurashima, Tomoharu Iwata, Go Irie, and Ko Fujimura. 2010. Travel route recommendation using geotags in photo sharing sites. In *Proceedings of the 19th ACM International Conference on Information and Knowledge Management (CIKM'10)*. 579–588.

[15] Takeshi Kurashima, Tomoharu Iwata, Go Irie, and Ko Fujimura. 2013. Travel route recommendation using geotagged photos. *Knowledge and Information Systems* 37, 1 (2013), 37–60.

[16] Kwan Hui Lim, Jeffrey Chan, Shanika Karunasekera, and Christopher Leckie. 2017. Personalized Itinerary Recommendation with Queuing Time Awareness. In *Proceedings of the 40th International ACM SIGIR Conference on Research and Development in Information Retrieval (SIGIR'17)*. 325–334.

[17] Kwan Hui Lim, Jeffrey Chan, Shanika Karunasekera, and Christopher Leckie. 2018. Tour Recommendation and Trip Planning using Location-based Social Media: A Survey. *Knowledge and Information Systems* (2018).

[18] Kwan Hui Lim, Jeffrey Chan, Christopher Leckie, and Shanika Karunasekera. 2018. Personalized Trip Recommendation for Tourists based on User Interests, Points of Interest Visit Durations and Visit Recency. *Knowledge and Information Systems* 54, 2 (2018), 375–406.

[19] Claudio Lucchese, Raffaele Perego, Fabrizio Silvestri, Hossein Vahabi, and Rossano Venturini. 2012. How random walks can help tourism. In *Proceedings of the 34th European Conference on Information Retrieval (ECIR'12)*. 195–206.

[20] Ioannis Refanidis, Christos Emmanouilidis, Ilias Sakellariou, Anastasios Alexiadis, Remous-Aris Koutsiamanis, Konstantinos Agnantis, Aimilia Tasidou, Fotios Kokkoras, and Pavlos S. Efraimidis. 2014. myVisitPlanner GR: Personalized Itinerary Planning System for Tourism. In *Proceedings of the 8th Hellenic Conference on Artificial Intelligence (SETN'14)*. 615–629.

[21] Kendall Taylor, Kwan Hui Lim, and Jeffrey Chan. 2018. Travel Itinerary Recommendations with Must-see Points-of-Interest. In *Proceedings of the 2018 Web Conference Companion (WWW'18)*. 1198–1205.

[22] Bart Thomee, David A. Shamma, Gerald Friedland, Benjamin Elizalde, Karl Ni, Douglas Poland, Damian Borth, and Li-Jia Li. 2016. YFCC100M: The New Data in Multimedia Research. *Commun. ACM* 59, 2 (2016), 64–73.

[23] Theodore Tsiligirides. 1984. Heuristic methods applied to Orienteering. *Journal of the Operational Research Society* 35, 9 (1984), 797–809.

[24] Pieter Vansteenwegen, Wouter Souffriau, Greet Vanden Berghe, and Dirk Van Oudheusden. 2011. The city trip planner: An expert system for tourists. *Expert Systems with Applications* 38, 6 (2011), 6540–6546.

[25] Pieter Vansteenwegen, Wouter Souffriau, and Dirk Van Oudheusden. 2011. The Orienteering problem: A survey. *European Journal of Operational Research* 209, 1 (2011), 1–10.

[26] Xiaoting Wang, Christopher Leckie, Jeffery Chan, Kwan Hui Lim, and Tharshan Vaithianathan. 2016. Improving Personalized Trip Recommendation to Avoid Crowds Using Pedestrian Sensor Data. In *Proceedings of the 25th ACM International Conference on Information and Knowledge Management (CIKM'16)*. 25–34.

[27] Wolfgang Wörndl and Alexander Hefele. 2016. Generating Paths Through Discovered Places-of-Interests for City Trip Planning. In *Information and Communication Technologies in Tourism*. Springer International Publishing, 441–453.

[28] Yahoo! Webscope. 2014. Yahoo! Flickr Creative Commons 100M Dataset (YFCC-100M). http://webscope.sandbox.yahoo.com/catalog.php?datatype =i&did=67.

[29] Chenyi Zhang, Hongwei Liang, and Ke Wang. 2016. Trip Recommendation Meets Real-World Constraints: POI Availability, Diversity, and Traveling Time Uncertainty. *ACM Transactions on Information Systems* 35, 1 (2016), 5.

[30] Chenyi Zhang, Hongwei Liang, Ke Wang, and Jianling Sun. 2015. Personalized Trip Recommendation with POI Availability and Uncertain Traveling Time. In *Proceedings of the 24th ACM International Conference on Information and Knowledge Management (CIKM'15)*. 911–920.